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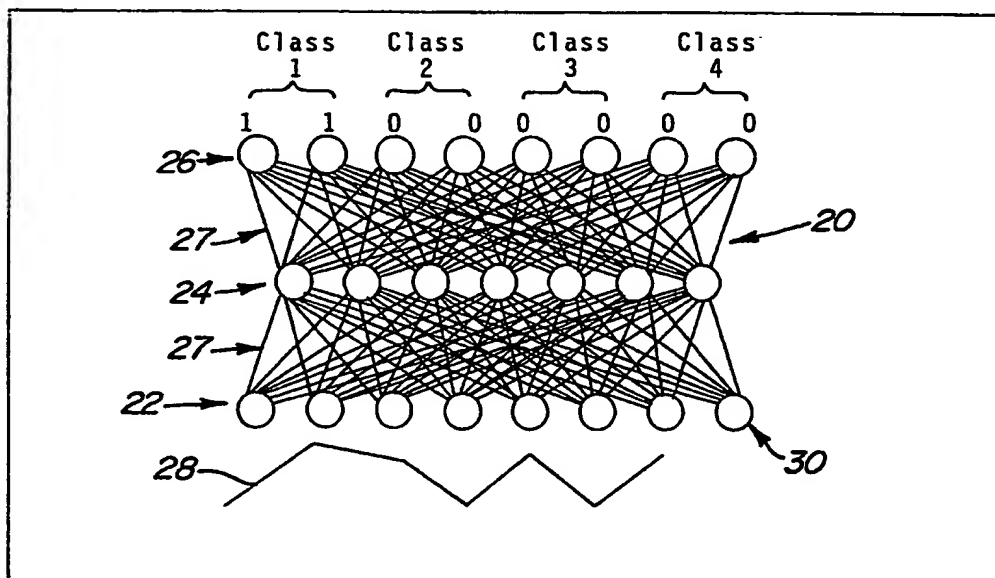
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(54) Title: ADAPTIVE NETWORK FOR CLASSIFYING TIME-VARYING DATA



(57) Abstract

An information processor (20) for classifying a set of two-dimensional data. The data represents information from at least two domains. The processor (20) utilizes a neural network architecture having at least $N + 1$ input neurons (22), where N is the number of values in the first domain. The network (22) is trained to produce an output state that classifies a plurality of input signals belonging to a particular class. In the preferred embodiment the second domain is time.

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ADAPTIVE NETWORK FOR CLASSIFYING TIME-VARYING DATA

1 Background of the Invention1. Technical Field

 This invention relates to information
processors and, more particularly, to a method and
5 apparatus for classifying time varying data.

2. Discussion

 Classifying of complex time-varying data
poses a number of difficult problems for conventional
information processors. The task of classification
10 typically involves recognizing patterns typical of
known classes from large amounts of two-dimensional
data. Where the patterns to be recognized have subtle
variations between the known classes, traditional
classifiers often fail to correctly distinguish between
15 the classes. This is due, in part, to the strong
assumptions which must be made concerning the
underlying distributions of the input data. Algorithms
must then be developed to extract these features and to
match known features with the input features for
20 classification.

 The success of the classifier is dependent on
the correctness of these underlying assumptions. Many
problems are not susceptible to explicit assumptions in
algorithms, due to the subtlety of the patterns
25 involved, as well as the wide variations of such
patterns within each class. A further disadvantage

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1 with traditional classifiers is the extensive
preprocessing normally required and the extensive time
required to develop the algorithm and software to
accomplish the pattern matching. Examples of such
5 classification problems include classifying time
varying signals from various sources such as speech,
image data, radar, sonar, etc. Also, conventional
information processor are generally not fault tolerant,
and cannot handle certain variations in the input
10 signals such as changes in the orientation of a visual
pattern, or differences in speakers, in the case of
speech recognition.

In recent years it has been realized that
conventional Von Neumann computers, which operate
15 serially, bear little resemblance to the parallel
processing that takes place in biological systems such
as the brain. It is not surprising, therefore, that
conventional information classification techniques
should fail to adequately perform the pattern
20 recognition tasks performed by humans. Consequently,
new methods based on neural models of the brain are
being developed to perform perceptual tasks. These
systems are known variously as neural networks,
neuromorphic systems, learning machines, parallel
25 distributed processors, self-organizing systems, or
adaptive logic systems. Whatever the name, these
models utilize numerous nonlinear computational
elements operating in parallel and arranged in patterns
reminiscent of biological neural networks. Each
30 computational element or "neuron" is connected via
weights or "synapses" that typically are adapted during
training to improve performance. Thus, these systems
exhibit self-learning by changing their synaptic
weights until the correct output is achieved in
35 response to a particular input. Once trained, neural

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1 nets are capable of recognizing a pattern and producing
a desired output even where the input is incomplete or
hidden in background noise. Also, neural nets exhibit
greater robustness, or fault tolerance, than Von
5 Neumann sequential computers because there are many
more processing nodes, each with primarily local
connections. Damage to a few nodes or links need not
impair overall performance significantly.

There are a wide variety of neural net models
10 utilizing various topologies, neuron characteristics,
and training, or learning, algorithms. Learning
algorithms specify an internal set of weights and
indicate how weights should be adapted during use, or
training, to improve performance. By way of
15 illustration, some of these neural net models include
the Perceptron, described in U.S. Patent No. 3,287,649
issued to F. Rosenblatt; the Hopfield Net, described in
U.S. Patent Nos. 4,660,166 and 4,719,591 issued to J.
Hopfield; the Hamming Net and Kohohonen self-organizing
20 maps, described in R. Lippman, "An Introduction to
Computing with Neural Nets", IEEE ASSP Magazine, April
1987, pages 4-22; and "The Generalized Delta Rule for
Multilayered Perceptrons", described in Rumelhart,
Hinton, and Williams, "Learning Internal
25 Representations by Error Propagation", in D. E.
Rumelhart and J. L. McClelland (Eds.), Parallel
Distributed Processing; Explorations in the
Microstructure of Cognition. Vol. 1: Foundation. MIT
Press (1986).

30 While each of these neural net models achieve
varying degrees of success at the particular task to
which it is best suited, a number of difficulties in
classifying time-varying data still are encountered
when using neural network processors. For example,
35 where the time-varying data is complex and involves

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1 large quantities of data, a major problem is in
developing a technique for representing the data to the
neural network for processing. For example, in
classifying radar or sonar doppler time signatures from
5 objects, the minimum amount of data required to
adequately represent classifications may involve, for
example, fifty time slices of sixteen frequency bands
of the doppler data. One way to present this data to a
neural net processor would be to utilize a neural
10 network with 800 ($50 + 16$) input neurons and to present
each of the 800 input neurons with one sample of
doppler data. The disadvantage of this approach is
that such a large number of input neurons and the
corresponding large number of total neurons and
15 interconnections would result in a neural network that
is very complex and expensive. Further, such a complex
network takes a greater period of time to process
information and to learn.

Thus, it would be desirable to provide a
20 processor for classifying time-varying data with a
minimum of preprocessing and requiring a minimum of
algorithm and software development. It would also be
desirable to provide a classification processor that is
not based on explicit assumptions but instead can adapt
25 by training to recognize patterns. It would also be
desirable to provide a means for representing
time-varying data to an adaptive processor in a
simplified manner which reduces the total number of
input values presented to the processor.

30 SUMMARY OF THE INVENTION

In accordance with the teachings of the
present invention, an adaptive network is provided with
at least $N + 1$ input neurons, where N equals the number
of values in a first domain associated with a given

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1 value in a second domain. The processor receives one
of each of the N values in the first domain in the
input neurons, and receives a single associated value
from a second domain in the remaining input neuron.
5 The network is trained using known training data to
produce an output that serves to classify the known
data. The network training is repeated for each value
in the second domain by presenting that value together
with each of the N values in the first domain as input.
10 Once trained, the adaptive network will produce an
output which classifies an unknown input when that
input is from a class the adaptive network was trained
to recognize.

BRIEF DESCRIPTION OF THE DRAWINGS

15 The various advantages of the present
invention will become apparent to those skilled in the
art after reading the following specification and by
reference to the drawings in which:

FIG. 1 (A-D) are representative doppler
20 signatures from four classes of multiple moving
objects;

FIG. 2 is a diagram of the adaptive network
in accordance with the teachings of the present
invention; and

25 FIG. 3 is a representation of doppler data
for four classes of objects; and

FIG. 4 is a drawing of an additional
embodiment of the present invention.

DESCRIPTION OF THE PREFERRED EMBODIMENT

30 In accordance with the teaching of the
present invention, a method and apparatus is provided
for classifying two-dimensional data. The
two-dimensional data can be derived from a variety of

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1 signal sources such as infrared, optical, radar, sonar,
etc. The data may be raw, that is unprocessed, or it
may be processed. One example of such processing is
5 doppler processing, wherein the difference in frequency
between an outgoing and an incoming signal is analyzed.
In general, if the object reflecting the transmitted
energy back is stationary with respect to the source
there will be no shift in frequency observed in the
returning energy. If the object is moving toward the
10 source, the reflected energy will have a higher
frequency, and if the object is moving away, the
reflected energy will be lowered in frequency.

In FIGS. 1(A-D) four doppler signatures from
four different classes of objects are shown. In these
15 figures the doppler frequency, that is, the shift in
frequency in the returning object or objects is
represented along the horizontal axis. Time is
represented along the vertical axis. It can be seen
that FIGS. 1(A-D) each have a characteristic shape or
20 pattern. The fact that the pattern changes from the
lower portion of each figure to the upper portion,
indicates changes in the detected doppler frequencies
over time. This would indicate changes in the motion
of multiple objects in the particular instance for each
25 of the four classes of objects.

It should be noted that two different
instances of multiple objects within a given class will
have a doppler signature which resembles, but is not
exactly identical, to each other. Thus, while it may
30 be relatively easy for an observer, upon visual
inspection, to identify a doppler signature from a
given class, because of the subtle variations from
instance to instance within a different class, it is
difficult, if not impossible, for conventional
35 processors to correctly identify the class of a doppler

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1 signature. For this reason the pattern recognition
capabilities of a neural network would seem to be well
suited to solving the doppler time signature
classifying problem. However, one problem that is
5 encountered is that due to practical limitations in the
number of neurons in working neural networks, it would
be difficult to provide a neural network with all of
the information contained in the doppler signatures
shown in FIGS. 1(A-D). To simplify the information,
10 one could compress the data to its most essential
characteristics. In this way, the data would be
reduced to manageable proportions for processing by a
neural network.

Accordingly, In FIG. 3 there is shown a
15 representative simplified doppler signature for four
different classes of objects. As in FIGS. 1(A-D), the
horizontal axis represents the doppler frequency and
the vertical axis represents time. Each horizontal
line 10 in FIG. 3 represents the doppler frequencies
20 received at a given time. There are 32 horizontal
lines in FIG. 3, each representing a time slice of the
doppler signal. The doppler signals in FIG. 3 are
divided by means of vertical lines into four classes; a
first class 12, a second class 14, a third class 15 and
25 a fourth class 18. Like the four classes shown in
FIGS. 1(A-D), the four classes in FIG. 3 represent
doppler signals from four different types of objects
and each have a pattern that is characteristic of that
object, or objects. Even though FIG. 3 represents much
30 more simplified doppler data than that shown in FIGS.
1(A-D), representation of the four patterns in FIG. 3
to a neural network would still involve a large amount
of data. In particular, each time slice 10 in each
class is drawn from doppler frequencies from 16
35 frequency bins. There are 32 time slices 10 for each

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1 class. Consequently, there would be 512 individual
pieces of information for each class. Using
conventional neural network techniques, a neural
network having 512 input neurons might be required to
5 process all of the information in each class shown in
FIG. 3.

In order to simplify the representation of
this data for presentation to the neural network, in
accordance with the present invention, the data shown
10 in FIG. 3 may be represented as indicated by FIG. 2.
In FIG. 2 an adaptive network 20 in accordance with the
preferred embodiment of the present invention is shown.
The adaptive network 20 utilizes a conventional neural
network architecture known as a multilayer perceptron.
15 It will be appreciated by those skilled in the art that
a multilayer perceptron utilizes a layer of input
neurons 22, one or more layers of inner neurons 24 and
a layer of output neurons 26. Each neuron in each
layer is connected to every neuron in the adjacent
20 layer by means of synaptic connections 27, but neurons
in the same layer are not typically connected to each
other. Each neuron accepts as input either a binary or
a continuous-valued input and produces an output which
is some transfer function of the inputs to that neuron.
25 The multilayer perceptron shown in FIG. 2 may be
trained by the conventional back propagation technique
as is known in the art. This technique is described in
detail in the above-mentioned article by D. E.
Rumelhart and J. L. McClelland, which is incorporated
30 herein by reference.

In accordance with the present invention the
adaptive network 20 is configured so that it has a
particular number of input neurons 22 determined by the
input data. In particular, in the example in FIG. 2,
35 the doppler data contains seven frequency bins. It

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1 will be appreciated that, for example, in FIG. 3 there
will be 16 frequency bins, and that the number of
doppler frequency bins will depend on the particular
data to be analyzed, and the desired complexity of the
5 adaptive network 20.

The doppler frequency curve 28, like the
doppler frequency curves in FIG. 3, represents one time
slice of doppler data. That is, it represents the
doppler frequencies received at a given time. It is
10 preferred that the range of frequencies be normalized
so that they may be represented by a signal within a
range that is acceptable to the input neurons 22. For
example, the doppler frequencies may be normalized to
have particular relative values between zero and one.

15 As shown in FIG. 2, seven input neurons each
receive a single doppler frequency value from the
doppler frequency curve 28. An eighth input neuron 30
receives a signal which is representative of the time
at which the doppler frequency curve 28 was received.
20 The magnitude of the signal used for the time input
neuron 30 may be normalized so that the entire range of
time values falls within the acceptable range for the
input neuron 22. For example, in the data from FIG. 3
there are 32 doppler frequency curves from 32 different
25 time slices and these times may simply be numbered 1
through 32 wherein the range 1 through 32 is normalized
for the signal transmitted to input neuron 30. When
the doppler frequency curve 28, together with the time
is transmitted to the input neurons 22 and 30, the
30 adaptive network 20 will produce some output state at
its output neurons 26. To train the adaptive network
20 to produce a desired output, the learning algorithm
known as backward error propagation may be used. In
this technique a known doppler frequency and time input
35 will be presented to the input neurons and the adaptive

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1 network 20 will be trained to produce an output
corresponding to the class of the doppler frequency
curve. For example, assuming that the training input
is from a first class, the desired output may be to
5 have the first two output neurons 26 produce binary
ones and all the other output neurons produce binary
zero values. After repeated training procedures the
adaptive network 20 will adapt the weights of the
synaptic connections 27 until it produces the desired
10 output state. Once the adaptive network 20 is trained
with the first doppler frequency curve 28 at a first
time slice, it may then be trained for all the
successive time slices. For example, the adaptive
network 20 may be trained for each of the 32 doppler
15 frequency curves 10 in FIG. 3 to produce an output
indicating the first class. Once the training for the
first class is complete, an unknown set of doppler
frequency curves and times may be transmitted to the
adaptive network 20. If the unknown doppler signature
20 has the general characteristics of that of the first
class, the adaptive network 20 will produce an output
state for each time slice corresponding the first
class.

Further, the adaptive network 20 may be
25 trained to recognize multiple classes of doppler
signatures. To accomplish this, the steps used to
train the adaptive network 20 to recognize the first
class of doppler frequency curves is simply repeated
for the second, third and fourth classes. As shown in
30 FIG. 2, the adaptive network 20 may be trained to
indicate the second, third and fourth classes by
producing binary ones in the output neurons 26
associated with those classes as indicated in FIG. 2.
The number of classes which the adaptive network 20 may
35 be trained to recognize will depend on a number of

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1 variables such as the complexity of the doppler
signals, and the number of neurons, layers and
interconnections in the adaptive network 20.

Referring now to FIG. 4, an adaptive network
5 20 in accordance with the present invention is shown.
This embodiment is similar to the one shown in FIG. 2,
except that it utilizes 18 input neurons 22, 24 inner
neurons 24 and 26 output neurons 26. It will be
appreciated that with a larger number of neurons and
10 synaptic connections 27, time-varying data of greater
complexity can be classified.

Once the adaptive network 20 has been trained
it could be reproduced an unlimited number of times by
making a copy of the adaptive network 20. For example
15 the copies may have identical, but fixed weight values
for the synaptic connections 27. In this way, mass
production of adaptive networks 20 is possible without
repeating the training process.

In view of the foregoing, those skilled in
20 the art should appreciate that the present invention
provides an adaptive network that can be used in a wide
variety of applications. The various advantages should
become apparent to those skilled in the art after
having the benefit of studying the specification,
25 drawings and following claims.

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CLAIMSWhat is Claimed is:

1 1. An information processor (20) for
classifying a set of two-dimensional data, said data
representing information from at least two domains,
including a first and second domain, said information
5 processor including a network of neurons including
input (22) and output (26) neurons, there being at
least $N + 1$ input neurons, a plurality of synaptic
connections (27) providing weighted interconnections
between selected ones of said neurons, characterized
10 by:

 said network (20) having at least $N + 1$ input
neurons (22), where N is the number of values in said
first domain;

 means for transmitting a set of input signals
15 to said input neurons (22), each signal being received
by at least one input neuron, said set of input signals
including at least a single value from said second
domain, and said set of input signals also including N
values from said first domain, said N values all being
20 associated with said single value in said second
domain; and

 means for training (22, 24, 26) said network
(20) to produce a desired output including means for
presenting a known input signal to said input neurons
25 (22, 30), and means for adjusting (24, 26) said
weighted synaptic interconnections (27) in repeated
training sessions to cause said network (20) to produce
said desired output.

1 2. The information processor (20) of Claim
1 wherein said second domain is time, and the N values
from the first domain associated with a given time
value represents the values of those N values at a
5 given time.

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- 1 3. The information processor of Claim 2
 wherein said second domain represents doppler data.
- 1 4. The information processor of Claim 3
 wherein said classification represents different types
 of objects from which said doppler signals originate.
- 1 5. The information processor of Claim 1
 wherein the total number of input neurons (22) is $N + 1$.
- 1 6. The information processor of Claim 1
 wherein said desired output represents a classification
 for a plurality of said known input signals.
- 1 7. The information processor of Claim 1
 wherein said means for training said network (24, 26)
 trains said network with multiple input signals that
 include a plurality of inputs from the second domain
5 along with the associated N inputs from the first
 domain.

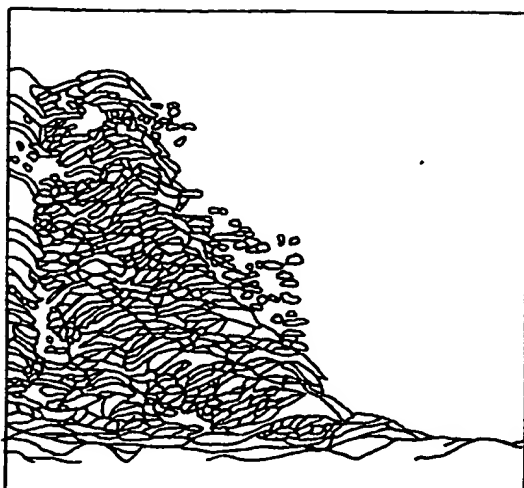


Fig-1A

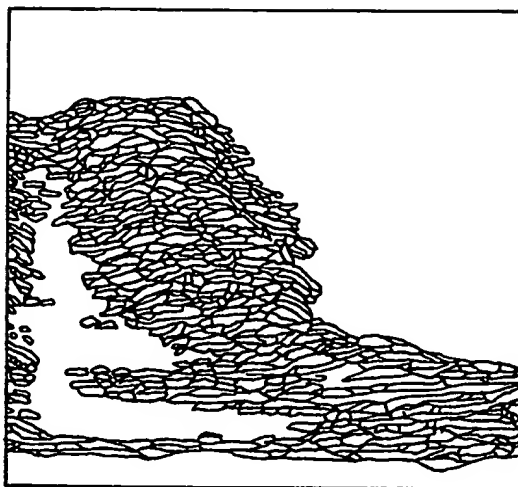


Fig-1B

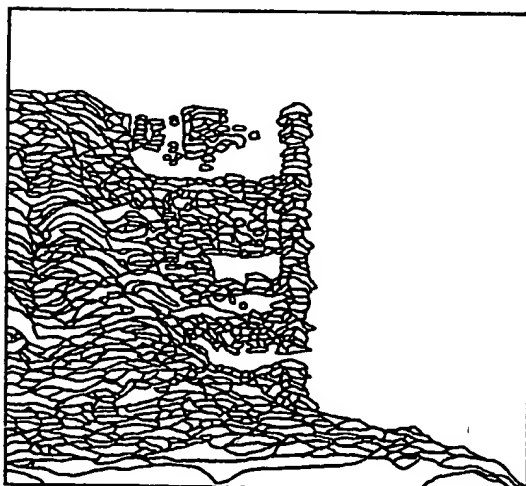


Fig-1C

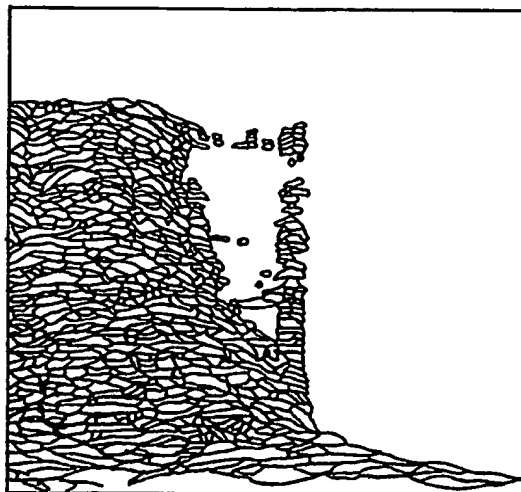


Fig-1D

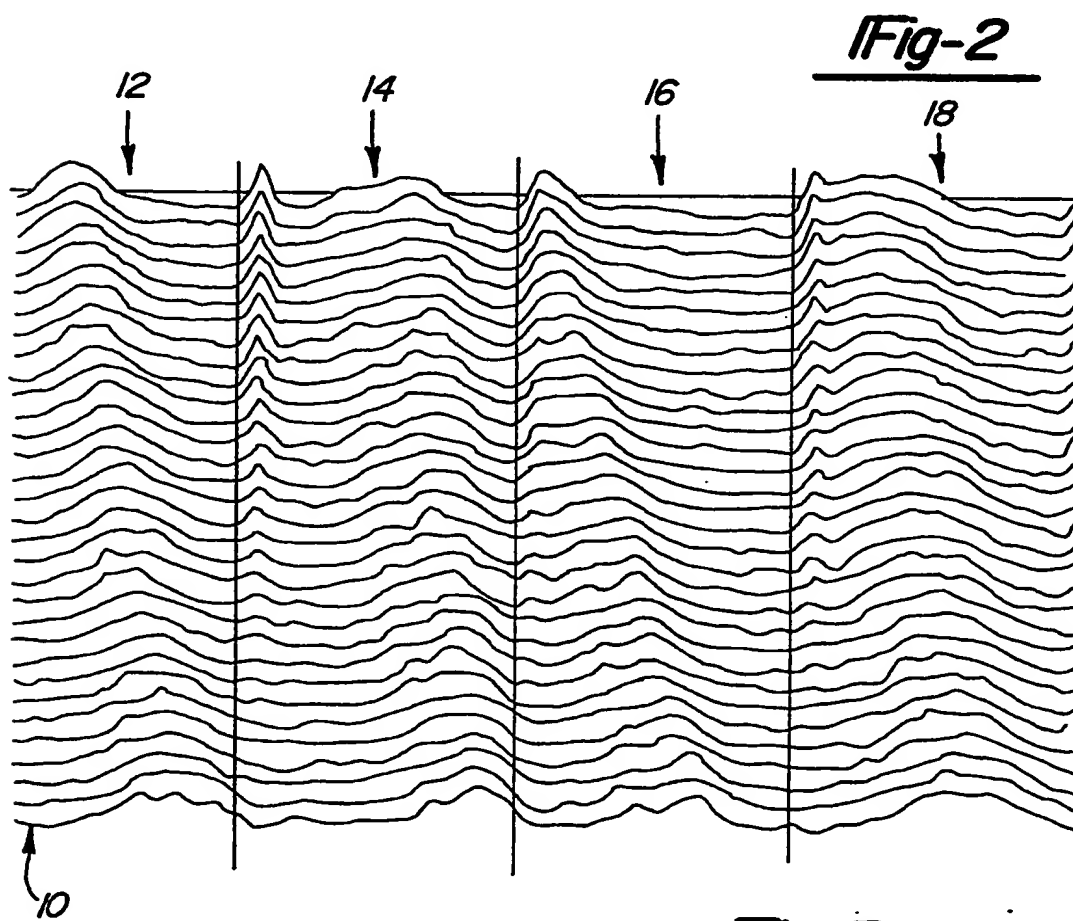
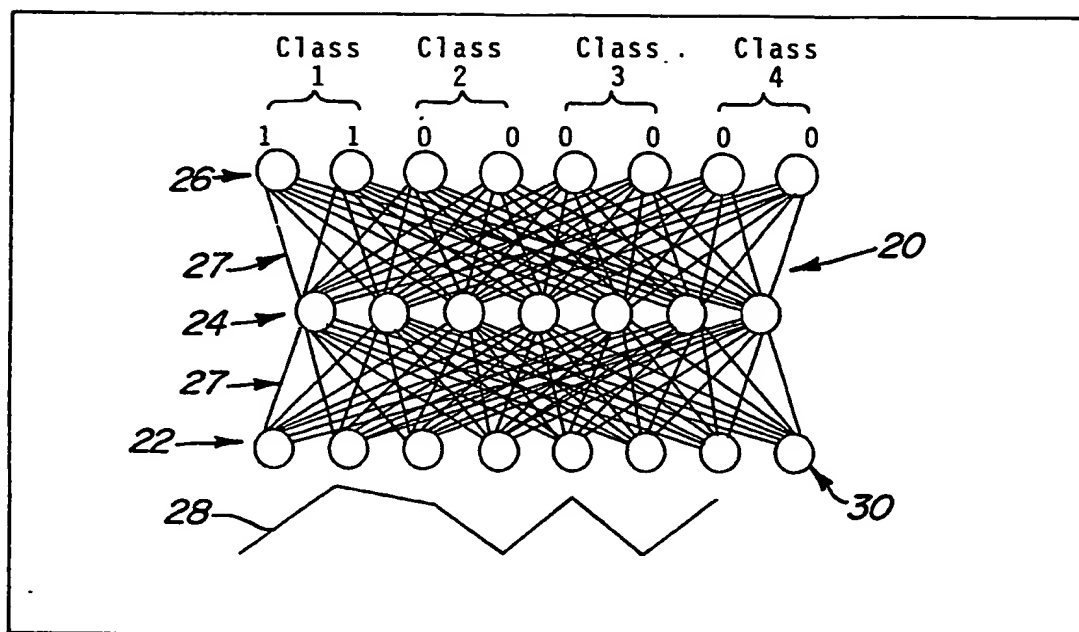
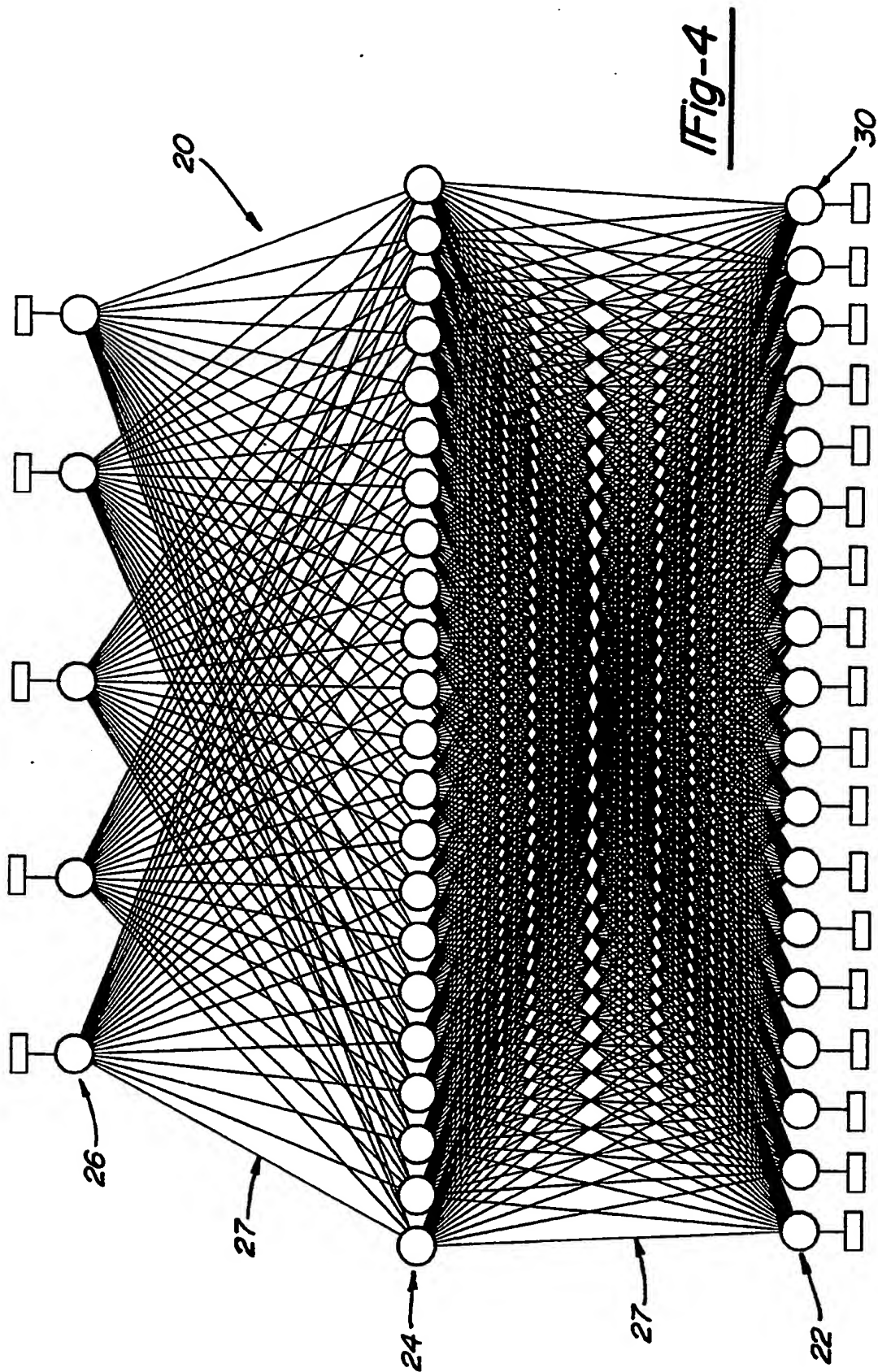


Fig-3



INTERNATIONAL SEARCH REPORT

International Application No PCT/US 90/04487

I. CLASSIFICATION OF SUBJECT MATTER (if several classification symbols apply, indicate all) ⁸ According to International Patent Classification (IPC) or to both National Classification and IPC IPC ⁵ : G 06 F 15/80, G 01 S 7/02											
II. FIELDS SEARCHED <div style="text-align: center; border-top: 1px solid black; border-bottom: 1px solid black; margin: 5px 0;">Minimum Documentation Searched ⁷</div> <table style="width: 100%; border-collapse: collapse;"> <tr> <th style="width: 20%; border-bottom: 1px solid black;">Classification System</th> <th style="border-bottom: 1px solid black;">Classification Symbols</th> </tr> <tr> <td style="border-right: 1px solid black; padding: 5px;">IPC⁵</td> <td style="padding: 5px;">G 06 F 15/80, G 01 S 7/02</td> </tr> </table> <div style="border-top: 1px solid black; padding-top: 5px; margin-top: 5px;"> Documentation Searched other than Minimum Documentation to the Extent that such Documents are Included in the Fields Searched ⁸ </div>			Classification System	Classification Symbols	IPC ⁵	G 06 F 15/80, G 01 S 7/02					
Classification System	Classification Symbols										
IPC ⁵	G 06 F 15/80, G 01 S 7/02										
III. DOCUMENTS CONSIDERED TO BE RELEVANT ⁹ <table style="width: 100%; border-collapse: collapse;"> <tr> <th style="width: 10%; border-bottom: 1px solid black;">Category ⁹</th> <th style="border-bottom: 1px solid black;">Citation of Document, ¹¹ with indication, where appropriate, of the relevant passages ¹²</th> <th style="width: 15%; border-bottom: 1px solid black;">Relevant to Claim No. ¹³</th> </tr> <tr> <td style="border-right: 1px solid black; vertical-align: top; padding: 5px;">X</td> <td style="border-right: 1px solid black; padding: 5px;"> IEEE International Conference on Neural Networks, San Diego, California, 24-27 July 1988, P.F. Castelaz: "Neural networks in defense applications", pages 473-480 see page 476, lines 10-31; figure 2 -- </td> <td style="vertical-align: top; padding: 5px;">1-7</td> </tr> <tr> <td style="border-right: 1px solid black; vertical-align: top; padding: 5px;">A</td> <td style="border-right: 1px solid black; padding: 5px;"> IJCNN International Joint Conference on Neural Networks, Sheraton Washington Hotel, 19-22 June 1989, A. Khotanzad et al.: "Target detection using a neural network based passive sonar system", pages I-335-I-340 see abstract; page I-336, column 1, lines 15-32; column 2, lines 30-36; pages I-337, column 1, lines 1-31; column 2, lines 35-49; figure 2 -- <div style="text-align: center; margin-top: 10px;">./.</div> </td> <td style="vertical-align: top; padding: 5px;">1-7</td> </tr> </table>			Category ⁹	Citation of Document, ¹¹ with indication, where appropriate, of the relevant passages ¹²	Relevant to Claim No. ¹³	X	IEEE International Conference on Neural Networks, San Diego, California, 24-27 July 1988, P.F. Castelaz: "Neural networks in defense applications", pages 473-480 see page 476, lines 10-31; figure 2 --	1-7	A	IJCNN International Joint Conference on Neural Networks, Sheraton Washington Hotel, 19-22 June 1989, A. Khotanzad et al.: "Target detection using a neural network based passive sonar system", pages I-335-I-340 see abstract; page I-336, column 1, lines 15-32; column 2, lines 30-36; pages I-337, column 1, lines 1-31; column 2, lines 35-49; figure 2 -- <div style="text-align: center; margin-top: 10px;">./.</div>	1-7
Category ⁹	Citation of Document, ¹¹ with indication, where appropriate, of the relevant passages ¹²	Relevant to Claim No. ¹³									
X	IEEE International Conference on Neural Networks, San Diego, California, 24-27 July 1988, P.F. Castelaz: "Neural networks in defense applications", pages 473-480 see page 476, lines 10-31; figure 2 --	1-7									
A	IJCNN International Joint Conference on Neural Networks, Sheraton Washington Hotel, 19-22 June 1989, A. Khotanzad et al.: "Target detection using a neural network based passive sonar system", pages I-335-I-340 see abstract; page I-336, column 1, lines 15-32; column 2, lines 30-36; pages I-337, column 1, lines 1-31; column 2, lines 35-49; figure 2 -- <div style="text-align: center; margin-top: 10px;">./.</div>	1-7									
<div style="display: flex; justify-content: space-between;"> <div style="width: 45%;"> <p>¹⁰ Special categories of cited documents:</p> <p>"A" document defining the general state of the art which is not considered to be of particular relevance</p> <p>"E" earlier document but published on or after the international filing date</p> <p>"L" document which may throw doubts on priority claim(s) or which is cited to establish the publication date of another citation or other special reason (as specified)</p> <p>"O" document referring to an oral disclosure, use, exhibition or other means</p> <p>"P" document published prior to the international filing date but later than the priority date claimed</p> </div> <div style="width: 45%;"> <p>"T" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention</p> <p>"X" document of particular relevance; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step</p> <p>"Y" document of particular relevance; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents, such combination being obvious to a person skilled in the art.</p> <p>"&" document member of the same patent family</p> </div> </div>											
IV. CERTIFICATION <table style="width: 100%; border-collapse: collapse;"> <tr> <td style="width: 50%; border-bottom: 1px solid black; padding: 5px;"> Date of the Actual Completion of the International Search 13th November 1990 </td> <td style="width: 50%; border-bottom: 1px solid black; padding: 5px;"> Date of Mailing of this International Search Report <div style="text-align: right;">- 4. 12. 90</div> </td> </tr> <tr> <td style="border-bottom: 1px solid black; padding: 5px;"> International Searching Authority <div style="text-align: center; margin-top: 5px;">EUROPEAN PATENT OFFICE</div> </td> <td style="border-bottom: 1px solid black; padding: 5px;"> Signature of Authorized Officer <div style="display: flex; align-items: center; margin-top: 10px;"> <div style="flex: 1; text-align: center;"> </div> <div style="border: 1px solid black; padding: 2px 5px; margin-left: 10px;">M. PEIS</div> </div> </td> </tr> </table>			Date of the Actual Completion of the International Search 13th November 1990	Date of Mailing of this International Search Report <div style="text-align: right;">- 4. 12. 90</div>	International Searching Authority <div style="text-align: center; margin-top: 5px;">EUROPEAN PATENT OFFICE</div>	Signature of Authorized Officer <div style="display: flex; align-items: center; margin-top: 10px;"> <div style="flex: 1; text-align: center;"> </div> <div style="border: 1px solid black; padding: 2px 5px; margin-left: 10px;">M. PEIS</div> </div>					
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III. DOCUMENTS CONSIDERED TO BE RELEVANT (CONTINUED FROM THE SECOND SHEET)		
Category *	Citation of Document, " with indication, where appropriate, of the relevant passages	Relevant to Claim No.
A	IEEE First International Conference on Neural Networks, San Diego, California, 21-24 June 1987, H. Bôulard et al.: "Multilayer perceptrons and automatic speech recognition", pages IV-407-IV-416 see page IV-413, lines 3-20, page IV-414, lines 1-13; figure 2 -----	1-7